IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 12, No. 4, December 2023, pp. 2022~2032
ISSN: 2252-8938, DOI: 10.11591/ijai.v12.i4.pp2022-2032

High uncertainty aware localization and error optimization of mobile nodes for wireless sensor networks

Raja Thejaswini Nandyala, Muthupandi Gandhi
Department of ECE, School of Engineering, Presidency University, Bangalore, India

Article Info

Article history:

Received Oct 11, 2022
Revised Jan 25, 2023
Accepted Mar 10, 2023

Keywords:

High uncertainty
Least squared relative error
Localization
Mobile sensor nodes
Radio signal strength
Wireless sensor networks

ABSTRACT

The localization of mobile sensor nodes in a wireless sensor network (WSN) is a key research area for the speedy development of wireless communication and microelectronics. The localization of mobile sensor nodes massively depends upon the received signal strength (RSS). Recently, the least squared relative error (LSRE) measurements are optimized using traditional semidefinite programming (SDP) and the location of the mobile sensor nodes was determined using the previous localization methods like least squared relative error and semidefinite programming (LSRE-SDP), and approximate nonlinear least squares and semidefinite programming (ANLS-SDP). Therefore, in this work, a novel high uncertainty aware-localization error correction and optimization (HUA-LECO) model is employed to minimize the aforementioned problems regarding the localization of mobile sensor nodes and enhance the performance efficiency of root mean square error (RMSE) results. Here, the position of target mobile sensor nodes is evaluated based on the gathered measurements while discarding faulty data. Here, an iterative weight updation approach is utilized to perform localization based on Monte Carlo simulations. Simulation results show significant improvement in terms of RMSE results in comparison with traditional LSRE-SDP and ANLS-SDP methods under high uncertainty.

Corresponding Author:

Raja Thejaswini Nandyala
Department of ECE, School of Engineering, Presidency University
Bengaluru, India
Email: phdtej2k21@rediffmail.com

1. INTRODUCTION

Wireless sensor networks (WSNs) are a collection of a large number of sensor nodes that can communicate with each other in varied environmental conditions through wireless channels [1], [2] to measure physical changes. The distributed sensor nodes gather data related to their adjacent activities and events and share gathered information with the other nodes to the base station through cluster head (CH) node for further processing [3]. Moreover, there are numerous applications of WSNs in different fields and some of those fields are animal tracks, medical fields, environmental tracking, military task handling, oil exploration, fire identification, intruder identification, infrastructure management, disaster detection and situation handling, and tracking of sea animals and creatures [4]–[7]. In most of these mentioned applications, sensor nodes are placed in very harsh, unpredictable, unapproachable, and in such environments that humans cannot reach easily [8]. In these types of applications, sensor nodes are distributed in a random scattering style through aerial vehicles or some other way at the desired location. However, in these types of applications, accurate knowledge of node location is extremely important to detect the source of sensed information and to take required actions based on this obtained sensed information [9].

Furthermore, it is highly essential to have knowledge of the source of data generation to analyze sensed data. For an instance, in some cases, node positions remain static in a WSN environment and knowledge of installation points will make analysis easier and better. However, in some cases, node positions remain mobile, and these nodes change their position dynamically. Moreover, the use of mobile sensor nodes can enhance the scope of applications with several benefits like coverage and scalability enhancement and improves packet transmission rate. However, there can be a few limitations as well in the case of mobile sensor node utilization in terms of energy decay and uncertainty regarding the source of sensed data. Moreover, precise knowledge of the location of source data is a base for several applications like fraud detection systems, routing analysis, surveillance, and tracking. In dynamic WSNs, the sensor node position and location need to be identified dynamically, which can be an extremely complicated and tiresome task. Thus, localization in dynamic WSNs can be a significant research direction.

Therefore, precise geographic and sensor node position information has become an essential need in WSNs to perform multiple operations like environmental tracking, indoor navigation, and data gathering [10]–[12]. Additionally, multiple networking protocols, sensor node tracking, association, and geographical routing require precise knowledge of sensor node locations. However, adding global positioning system (GPS) receivers for every node is challenging and complicated due to their massive cost, hardware constraints, high power dissipation, and reduced performance due to shadowing effects. Besides, multiple localization detection techniques are developed in recent years by numerous researchers [13]. Some location detection techniques utilize few reference nodes and based on these adopted reference nodes, the location of an unknown node is identified [14]. Some of the measurement methods are angle of arrival (AoA), time of arrival (ToA), connectivity, and radio signal strength (RSS) [15], [16]. Among all these measurement or source location identification methods, RSS-based measurement is extremely effective due to the advantage of the ease of deployment and is less complex in nature. However, there are a few limitations regarding RSS-localization methods, which may cause high localization errors. The main limitation of the RSS method is the use of transmit power as a priori knowledge to identify node locations. However, the obtained transmit power is massively dependent on antenna gain and the battery status of sensor nodes. Thus, in real-time applications, transmit power may not remain steady which can lead to poor estimation regarding transmitted power [17], [18].

Recently, in [19], a fault-filtering method is adopted to identify fault-reference nodes so that localization error can be minimized. This technique mainly focuses on distance estimation for the implementation of the fault-filtering method based on the communication range of the nodes. In [20], a robustness enhanced sensor assisted Monte Carlo localization (RESA-MCL) method is adopted to identify the accurate position of mobile sensor nodes. Based on the node movements, RESA-MCL enhances the performance of the localization of sensor nodes. In [21], an extension of the distance vector-hop algorithm (DV-Hop) localization method is introduced as a regularized least square DV-Hop localization algorithm to enhance node localization accuracy based on statistical filtering optimization and the least square localization method. In [22], an anchor-assisted localization method is adopted to detect precise positions of mobile sensor nodes based on the transmission power control mechanism. However, a major limitation related to least square relative error (LSRE) approach is the presence of high uncertainty and high noise can change measured values drastically and remains extremely sensitive to outliers. Moreover, the traditional localization methods remain sensitive to the different environmental conditions like path loss and fading which can further enhance the noise factor. To overcome this challenge, a novel high uncertainty aware-localization error correction and optimization (HUA-LECO) model is adopted in this article to precisely identify the location of mobile sensor nodes. This work is an extension of the dynamic noisy measurement aware localization (DNMAL) model [23], in which the major focus was the minimization of the localization error of static sensor nodes with varying noise levels.The contribution of using the proposed HUA-LECO model is described.

– The HUA-LECO model performs extremely well in the case of inducing high uncertainty considering the dynamic mobility pattern of sensor nodes in the measurement model.
– Minimize localization error of mobile sensor node with a higher convergence rate. Thus, the HUA-LECO model can be utilized in different WSNs applications that require precise node localization data with higher accuracy and better performance in cases of high uncertainty regarding mobile sensor node position to accurately identify their position.
– The proposed HUA-LECO model shows a high-accuracy performance in terms of localization error minimization for both indoor and outdoor complex WSNs scenarios.
– Comparatively higher localization accuracy of mobile sensor nodes is achieved considering varied simulation parameters than state-of-art-localization error minimization methods like LSRE and semidefinite programming (SDP), even when some mobile sensor nodes provide faulty measurements and the impact on localization errors considering varied noise levels and the size of Monte Carlo simulations is also observed.

The paper is structured in the following style. Section 1, discusses the estimation of mobile sensor node localization and the significance of the proposed HUA-LECO model in WSNs. In section 2, a literature survey regarding the proposed HUA-LECO model and limitations of the existing localization detection methods are presented. In section 3, the methodology to reduce localization errors in dynamic WSNs is discussed. In section 4, the performance results of the HUA-LECO model are discussed and compared with traditional localization error minimization methods. Lastly, the percentage enhancement of the proposed HUA-LECO model is concluded and future enhancement of the HUA-LECO model is discussed.

2. LITERATURE SURVEY

This section studies some recent research works for performing localization in WSNs. In [24], node localization is achieved using uncertain data mapping in WSN applications based on RSS. Performance results are evaluated considering absolute mean localization error and compared against traditional localization methods. However, four beacon nodes are made static at the edges of the experimental WSN environment which may heavily affect accuracy results in the case of RSS attenuation and uncertainty of node position. In [25], a localization method in asynchronous WSNs is adopted based on time-of-flight (ToF). Here, localization accuracy results are obtained to compare against varied state-of-art-localization methods. However, in this method, beacon nodes are kept static in WSN. The calculation of the clock skews and localization capacity performance measurement is heavily dependent upon the centralized server. As a result, breaking down at one single centralized point can cause a system or server failure, and the complete localization process in WSN can be compromised.

In [26], a combined localization and synchronization method is introduced using time difference of arrival (TDoA) in asynchronous WSNs. Here, the localization process mainly depends upon the centralized server. The experimental results are performed on the basis of uncertainty in the position of anchor nodes. Therefore, similar to [25], breaking down centralized points can cause server failure. In [27], a node localization approach is performed on the basis of measurement of noise weighted least squares and error variance in an indoor environment. Here, a weighted approach is adopted based on the hybrid RSS/AoA measurements and utilizes three beacon nodes for localization measurements. However, faults in beacon node measurements can give faulty measurements. Another disadvantage is that the multipath fading and non-line of sight (NLoS) effects are not considered.

In [28], a Monte-Carlo localization (MCL) method is presented which is a range-free localization with no additional hardware complexities. Further, all the sensor nodes and beacon nodes move freely over time in a random manner. Here, a particle filter is used to enhance localization accuracy based on node mobility. Similarly, in [29], [30], MCL methods are adopted to enhance localization efficiency. However, the possibility of localization failure in these methods is high due to loss in connectivity and lower density of beacon nodes. This problem can be sorted by the sensor-assisted Monte Carlo localization (SA-MCL) method [31] which enhances the connectivity of beacon nodes in WSNs and handles the limitations of MCL methods. To improve localization accuracy [29] an enhanced MCL method is presented based on the differential evolution optimization (DEO) approach under low beacon density of sensor nodes. Here, the MCL-DE objective functions through sample weights instead of a regular sampling method. This method estimates valid samples for localization measurements. However, communication and computation cost are reasonably high. In [32], a neural network-based localization system is presented for WSNs in indoor scenarios to evaluate the position of Alzheimer's patients. Here, beacon nodes pre-dominantly utilize RSS to get the experimental results considering mean localization error. Here, beacon nodes are static and RSS samples are recorded to enhance connectivity. However, hardware needs to make this design more complex and the transformation of this approach for mobile nodes is a very complicated process. In [33], data aggregation and clustering-based methods are presented to improve the lifetime of the network based on the node localization and routing mechanism. In [34], a grid clustering method is presented to identify sensor node locations based on the genetic algorithm. In [35], a detailed review is performed to analyze localization problems and their performance. In the next section, solutions to avoid these addressed research limitations are presented in this paper namely a novel HUA-LECO model.

3. HUA-LECO MODEL FOR WIRELESS SENSOR NETWORKS

This section provides details of the methodology used to study the proposed HUA-LECO model for WSNs. First of all, the foremost aim of this work is an estimation of the mobile sensor nodes by accurately predicting their position based on the root mean square error (RMSE) when there is high uncertainty regarding the position of the sensor nodes. The second aim is the optimization of uncertainty-aware errors to precisely estimate the location of sensor devices. Here, mobile sensor nodes are used inside WSN which continuously

changes its position due to which strength of the radio signal varies with an unknown decay factor. These continuous RSS variations make localization of mobile sensor nodes quite difficult and challenging. Therefore, detailed mathematical modeling is presented in this section to achieve the desired objectives. Initially, the system model for the HUA-LECO model is discussed. Then, the mathematical modeling and working methodology of the HUA-LECO model is presented. At last, an algorithm for localization of sensor devices in case of high uncertainty through the HUA-LECO model is discussed in multiple steps.

3.1. System model

In this section, a system model is discussed for the detection of mobile sensor node location within WSN when the exact position of the sensor node is highly uncertain. Consider a WSN is formed and the number of sensor nodes deployed is S whose initial position is known prior, and later on; The position of the mobile sensor nodes is measured on the basis of radio signal strength (RSS) measurement computation from the sensor devices. All the measured information is gathered by a node namely the sink node and this node helps to predict the exact position of the desired node based on the RSS measurements. Then, the computation of RSS measurements from sensor nodes in a highly uncertain WSN environment is given by (1),

$$m_l = \|k - a_l\|_2 + \varphi_l, \quad l = 1, \dots, S, \tag{1}$$

Where the coordinates of the desired sensor node are given by $\boldsymbol{k} \in \mathbb{M}^{\boldsymbol{o}}$, the position of the $\boldsymbol{l^{th}}$ sensor node is given by $\boldsymbol{a_l} \in \mathbb{M}^{\boldsymbol{o}}$, uncertainty-aware errors are given by $\boldsymbol{\varphi_l}$ and these errors are identically distributed with the help of a random distribution parameter, Euclidean distance is given by the function $\|\cdot\|_{\mathbf{2}}$. Modeling considering highly uncertain mobile sensor node position can be handled using probability density function to analyze uncertainty-aware error correction estimates which can be defined using (2),

$$T(\varphi) = (1 - \lambda)\Psi(\varphi; 0, \mu^2) + \lambda\Gamma(\varphi). \tag{2}$$

Where uncertainty-aware measurement errors can be computed with the help of two different probability distributions such as one distribution is represented by $\Gamma(\varphi)$ whose probability is defined by λ and the second distribution is defined by $\Psi(\varphi; 0, \mu^2)$ whose probability is expressed by $1 - \lambda$. A highly uncertain position of sensor nodes can be modeled based on uncertainty-aware error correction estimates from $\Gamma(\varphi)$ and uncertainty-aware error correction estimates with zero means and μ^2 variance from $\Psi(\varphi; 0, \mu^2)$. Assume that λ is the ratio of uncertainty-aware error correction estimates to the overall measurement estimates from all the sensor devices. Furthermore, consider that the design of the proposed sensor node localization model relies minimum upon the uncertainty-aware error correction estimate value from probability distribution $\Gamma(\varphi)$.

Assume that only uncertainty-aware error correction estimates are considered to determine h from the measurements m_l where $l = 1, \dots \dots, M$. And the rest of the uncertainty-aware error measurement estimates are discarded. Moreover, the processing node does not have any idea about the sensor nodes which are giving error measurements and how their measurement distribution is processed in WSN. Consider that, the overall measurements obtained from all the sensor nodes, whether they are uncertainty-aware error correction estimates or uncertainty-aware error measurement estimates, or inappropriate estimates, are positive measurement values.

In several cases, the position of sensor nodes in WSN is determined using the least square bounding approach as discussed in [36], [37]. However, measured data in [36], [37] were noisy. Thus, these methods failed to provide an optimum solution to minimize measurement errors. Thus, an optimum solution is achieved to minimize measurement errors using the proposed dynamic noisy measurement aware localization (DNMAL) model which is our previous work [23] with the help of an improved least square bounding model. However, this work is an extension of the DNMAL model where the main objective is to obtain the optimum solution to get the exact position of the desired node in case of high uncertainties regarding their accurate localization due to the dynamic sensor node mobility patterns. This objective can be achieved with the help of the proposed HUA-LECO model by obtaining optimized weights. Then, the improved least square bounding model is given by the following equation. The problem is optimized to get the constrained minimization problem with the help of (3).

$$\min_{h} \sum_{l=1}^{M} (\|h - a_l\|_2^2 - m_l^2)^2. \tag{3}$$

$$\min_{h,} \sum_{l=1}^{M} (\Omega - 2a_l^W h + \|a_l\|^2 - m_l^2)^2, s.t\ \|a_l\|^2 = \Omega. \tag{4}$$

The traditional model utilizes Gaussian noise distribution as the noise distribution model. Here, Ω can be obtained through an optimization process and λ is obtained as the value of the uncertainty-aware error correction estimates with respect to the overall measurement estimates from (2). However, the main aim of the

proposed HUA-LECO model is to estimate the exact position of mobile sensor nodes based on the estimated error reduction which can be achieved by modeling the uncertainty-aware measurement error distribution $\Gamma(\varphi)$ in WSN. Then, the optimal solution related to the sensor node localization can be obtained by estimating (4) iteratively with the help of (5).

$$\Gamma(y,f) = \sum_{l=1}^{M} f_l(\tilde{a}_l^W y - b_l)^2 + \sum_{l=1}^{M} \beta^2 f_l - \ln f_l \tag{5}$$

Where the coefficient $\tilde{a}_l^W$ is determined using (6),

$$\tilde{a}_l^W = [-2a_l^W \ \ 1], \tag{6}$$

Then, parameter z is computed using (7),

$$y = [h \ \ \Omega]^W, \tag{7}$$

In the same way, b_l is determined using (8),

$$b_l = m_l^2 - \|a_l\|^2, \tag{8}$$

Here, the weight vector is defined by the parameter f where $f \in \mathbb{M}^M$ and f_l is computed as $f_l > 0, \forall l$. The aim of the proposed localization model is to optimize (5) using (9) respective to the parameters y and f,

$$\min_{y,f} \Gamma(y,f), \\ subject\ to\ y^W Cy + 2j^i y = 0, \tag{9}$$

Where $f_l > 0, \forall l$ and C is determined using (10),

$$C = \begin{bmatrix} L_z & E_{z*1} \\ E_{1*z} & E \end{bmatrix} \tag{10}$$

Where values of the weight matrix range from 0 to 1 and are defined with the help of $z \times 1$ and $1 \times z$ and j are determined using (11),

$$j = \begin{bmatrix} E_{z*1} \\ -D \end{bmatrix}. \tag{11}$$

Where the weights and the coefficient y can be updated with the help of $f_l^{(0)} = 1, \forall l$, and the solution to update the coefficient y for a specified $g-th$ iteration is given by (12),

$$y^{(g+1)} = arg\ min\ \Gamma\left(y, f^{(g)}\right), \\ subject\ to\ f_l > y^W Cy + 2j^W y = 0. \tag{12}$$

Similarly, the weights are updated using (13),

$$f^{(g+1)} = \arg\min \Gamma\left(y^{(g+1)}, f\right), \\ subject\ to\ f_l > 0, \forall l. \tag{13}$$

3.2. HUA-LECO model

This section provides details related to the mathematical representation of uncertainty-aware localization error optimization. This can be achieved by optimizing the problem of (12) with the help of the proposed HUA-LECO model. The optimization of (12) is performed by employing some constraints, objective functions, and gradients of the objective function on the basis of the Lipschitz continuity [38]. The optimization of the problem in (12) requires large computation and several iterations. Thus, the proposed HUA-LECO model is adopted to perform faster computations and handle a large number of iterations. Then, the value of coefficient $\boldsymbol{y}^{(g)}$ in every iteration gets updated using (14).

$$y^{(g)} = \arg\min_{y} \langle \chi_y \Gamma\left(\hat{y}^{(g)}, f^{(g-1)}\right), y - \hat{y}^{(g)} \rangle + n^{(g)} \left\|y - \hat{y}^{(g)}\right\|_2^2, \\ subject\ to\ f_l > y^W Cy + 2j^W y = 0. \tag{14}$$

Where parameter $\hat{y}^{(g)}$ is determined by (15),

$$\hat{y}^{(g)} = y^{(g-1)} + q^{(g)}\left(y^{(g-1)} - y^{(g-2)}\right) \tag{15}$$

Where constant for the Lipschitz continuity is given by $n^{(g)}$ of the function $\left[\chi_y \Gamma\left(y, f^{(g-1)}\right)\right]$ for $g-th$ iteration using (16),

$$n^{(g)}\|\rho - \varpi\| \geq \left\|\chi_y \Gamma\left(\rho, f^{(g-1)}\right) - \chi_y \Gamma\left(\varpi, f^{(g-1)}\right)\right\| \tag{16}$$

Where first term represents gradient magnitude controller of the objective function and second term represents descent of the objective function. Here, the Lipschitz constant is used as a constraint on the step size of the objective function. Here, parameter $\hat{y}^{(g)}$ is represented as a prediction estimate for the estimate $y^{(g)}$. With the help of prior iterations and trend estimation parameters, a prediction estimate $\hat{y}^{(g)}$ is obtained. Then, the trend estimation parameter is given by (17),

$$q^{(g)} = \frac{1}{12}\left(\frac{n^{(g-1)}}{n^{(g)}}\right) \tag{17}$$

Then, weights of f get updated by using (18),

$$f_g^{(l)} = \frac{1}{\left(j_l^{(g)}\right)^2 + \beta^2} \tag{18}$$

Where $j_l^{(g)}$ is evaluated using (19),

$$j_l^{(g)} = \tilde{a}_l^W y^{(g)} - b_l. \tag{19}$$

Then, the optimization problem in (14) can be minimized with the help of prediction estimate $\hat{y}^{(g)}$, parameter $n^{(g)}$, and coefficient C using (20),

$$\begin{gathered}\left(n^{(g)} L_{z+1} + \xi C\right) y^{(g)} = -D^W P^{(g-1)}\left(D\hat{y}^{(g)} - a\right) + n^{(g)}\hat{y}^{(g)} - \xi j \\ subject\ to\ {y^{(g)}}^W C y^{(g)} + 2j^W y^{(g)} = 0\end{gathered} \tag{20}$$

Where parameter ξ is defined using (21),

$$\xi \geq \max\left\{-n^{(g)}, -\left(\xi_1\left(C, D^W P^{(g-1)} D\right)\right)^{-1}\right\} \tag{21}$$

Where parameter ξ is adopted to update the value of y and f after finding the value of prediction estimate $\hat{y}^{(g)}$ in each iteration. Furthermore, a detailed step-by-step execution process for the exact localization of mobile sensor nodes by predicting and minimizing errors using the proposed HUA-LECO model is presented in Algorithm 1.

Algorithm 1. High uncertainty aware-localization error correction and optimization model

```
Input. a_l, m_l for l = 1,...,M, β, Λ†, & ψ
Step 1. Start.
Step 2. Estimate C,j,ŷ^(g),& q^(g) utilizing Eq. (10), (11), (15) and (17).
Step 3. Initialize P^(0),y^(-1) = y^(0) = D†a,n^(0) = 0 & g = 1.
Step 4. Iterate
Step 5.         n^(g) = 2‖D^W P^(g-1) D‖_J
Step 6.         q^(g) = (1/12)(n^(g-1)/n^(g))
Step 7.         ŷ^(g) = y^(g-1) + q^(g)(y^(g-1) - y^(g-2))
Step 7. Establish
          ξ* using y(ξ) = (n^(g) L_{z+1} + ξC)^(-1) - D^W P^(g-1)(Dŷ^(g) - a) + n^(g)ŷ^(g) - ξj
Step 8.         subject to y^(g)^W C y^(g) + 2j^W y^(g) = 0
Step 8.          Update y: y^(g) = y(ξ*).
Step 8.          Update f_g^(l) utilizing Eq. (18).
Step 9. Until convergence ‖y^(g) - y^(g-1)‖ < ψ or when Λ† is reached.
Step 10. Stop.
```

In this way, the proposed HUA-LECO Model determines the localization performance of mobile sensor nodes in case of high uncertainty regarding sensor node positions by estimating uncertainty-aware localization errors and optimizing uncertainty-aware localization errors. The minimization of uncertainty-aware localization errors is achieved and the impact of varying noise levels and size of Monte Carlo Simulations is discussed through the simulation study in next section. Further, results analysis is performed.

4. SIMULATION ANALYSIS AND RESULT

This section demonstrates performance results using the proposed HUA-LECO Model regarding the exact localization of mobile sensor nodes by minimizing localization RMSE error and compared against varied traditional localization models like approximate nonlinear least squares and semidefinite programming (ANLS-SDP) [39] and least squared relative error and semidefinite programming (LSRE-SDP) [36]. Furthermore, the performance of the proposed HUA-LECO Model in terms of localization error minimization is validated considering the baseline cramer-rao lower bound (CRLB) model for WSNs. MATLAB 2018a software is utilized for the implementation of the WSN models and the adopted system is configured with the specifications of 16 GB RAM and an Intel I-5 processor with NVIDIA graphics.

A generalized system is considered in this article for both indoor and outdoor applications and follows a uniform distribution into WSNs under a high-uncertainty environment and is used to track targets through cellular radio networks in WSNs. Localization of mobile sensor nodes under high uncertainty regarding their position is demonstrated in Figure 1 through a network model. Details of experimental configuration are kept the same as [36] for better analysis against the previous best localization methods. Here, all the sensor devices are placed in a uniform manner using a random distribution approach where the area of the WSN field is considered as $[-50, 50] \times [50{,}50]m^2$. A shadowing effect is also considered to determine RSS based on the approach presented in [36]. Additionally, Gaussian distribution is adopted with standard deviation as $\mu = 55\ m$. All the sensor measurements are taken using Gaussian distribution and sensor geometry is gathered using a location-operating network. The location of sensor nodes is measured under high uncertainties by varying sensor node size from 8 to 16. Here, the number of Monte Carlo Simulations used as 4,000 to generate a system model for WSN. It can be seen from the network model diagram that 2 sensor devices show faulty measurements and can be referred as outliers.

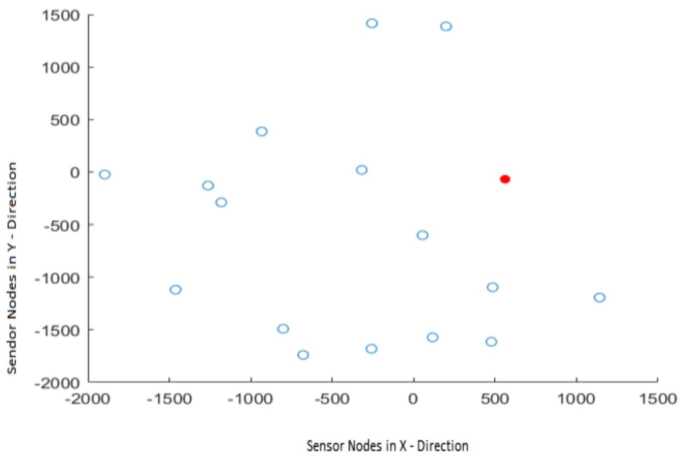

Figure 1. Localization of unknown mobile sensor node (i.e., red) in network model with multiple sensor nodes (i.e., blue)

The localization error is determined using (22),

$$RMSE = \sqrt{\frac{1}{\aleph_b}\sum_{\partial=1}^{\aleph_b}\left\|\hat{f}_\partial - f_\partial\right\|^2}, \tag{22}$$

where Monte Carlo Simulations are denoted by $\aleph_b$ and the number of Monte Carlo Simulations are used as default are 4,000. Actual positions of sensor devices are given by f_i and estimated positions of sensor devices are given by $\hat{f}_i$.

4.1. Scenario 1: performance by varying size of Monte Carlo simulations

Performance of the proposed HUA-LECO model is determined in terms of localization root mean square error with respect to the number of sensor nodes under high certainties regarding the position of desired unknown mobile sensor node and compared against existing localization error optimization methods like ANLS-SDP and LSRE-SDP. Here, the number of sensor devices and the number of Monte Carlo simulations are varied to get the performance efficiency and compared against traditional ANLS-SDP and LSRE-SDP methods. The main objective of this work is to identify position of an unknown mobile sensor node as shown in Figure 1 by varying the size of Monte Carlo simulations. In this experiment, the size of Monte Carlo Simulations is changed to 4,000, 6,000, and 8,000. At the same time, the number of sensor nodes varies from 8 to 16, and the noise level is kept at 8db. The localization error regarding the position of the unknown mobile sensor node is demonstrated in Figure 2 against varied number of sensor nodes when Monte Carlo Simulations are kept at 4,000. Similarly, when the size of $\aleph_b$ is changed to 6,000 iterations, the evaluated RMSE plot is demonstrated in Figure 3 for localizing the unknown mobile sensor device. Further, Figure 3 demonstrates the localization of the unknown mobile sensor node when the size of $\aleph_b$ is changed to 8,000 iterations. From all these graphs such as Figures 2 to 4 it is clear that the proposed HUA-LECO model minimizes the localization of unknown mobile sensor nodes significantly in comparison with existing localization methods ANLS-SDP and LSRE-SDP under high uncertainties and also satisfy the condition of generalized Cremer-lower bound. It is evident from Figures 2 to 4 results that RMSE is quite low in case of sensor node increment.

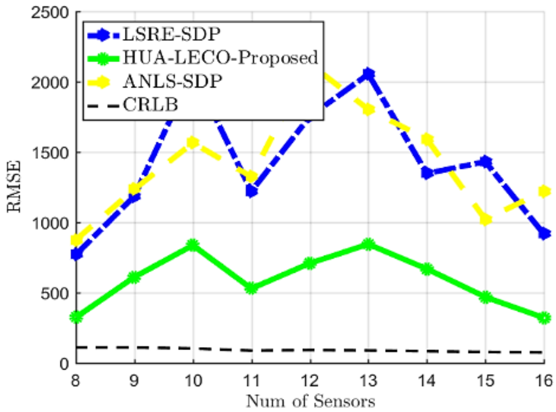

Figure 2. Comparison for RMSE against the number of sensor nodes considering different methods for Monte Carlo simulations as 4,000 iterations

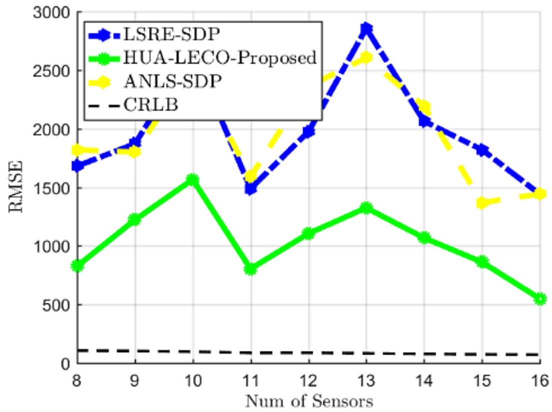

Figure 3. Comparison for RMSE against the number of sensor nodes considering different methods for Monte Carlo simulations as 6,000 iterations

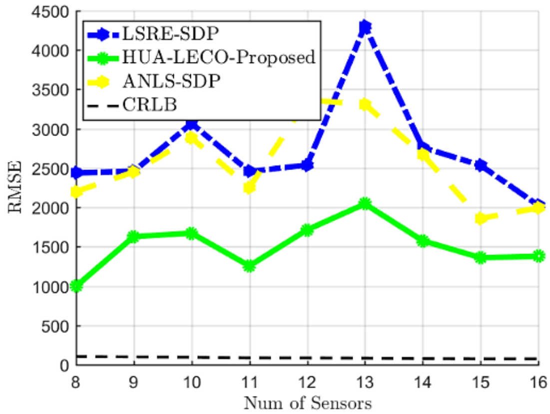

Figure 4. Comparison for RMSE against the number of sensor nodes considering different methods for Monte Carlo simulations as 8,000 iterations

4.2. Scenario 2: under varying noise levels

Here performance of the proposed HUA-LECO model is discussed based on the varying noise levels and keeping number of Monte Carlo simulations fixed in terms of RMSE against number of sensor nodes. Moreover, a simulation is performed by keeping Monte Carlo simulations as 4,000 and considering a noise level of 3dB, 5dB, 7dB, 9dB and number of sensor devices changes from 8 to 16. All the experiments are performed by setting up environment similar to [36]. Here, Figure 5 demonstrates the localization of mobile sensor nodes by evaluating RMSE for different number of sensor devices at noise level as 3dB. Similarly, similar to [36], Figure 6 shows the localization of mobile sensor nodes by determining RMSE for different number of sensor devices (8 to 16) at noise level as 5dB. In the same way, with reference to [36], Figure 7 demonstrates the localization of unknown mobile sensor nodes by determining RMSE for the different number of sensor devices (8 to 16) at noise levels as 7dB. Finally, the last simulation is performed considering a noise level of 9dB to evaluate mobile sensor node position in terms of RMSE against the varying number of sensor nodes from 8 to 16 as shown in Figure 8. It can be observed from Figure 5 to Figure 8 that with the increase in noise level, the localization errors vary for all the localization models. However, the variations in localization error with the increase in noise level using the proposed HUA-LECO model are significantly lower than in comparison with the previous best localization models ANLS-SDP and LSRE-SDP. Whereas, the localization error varies using ANLS-SDP and LSRE-SDP models is quite high. Therefore, it is evident from the performance results that the proposed HUA-LECO model provides significant results and minimizes localization errors compare to ANLS-SDP and LSRE-SDP models in terms of RMSE by varying noise levels to estimate the location of the mobile sensor device.

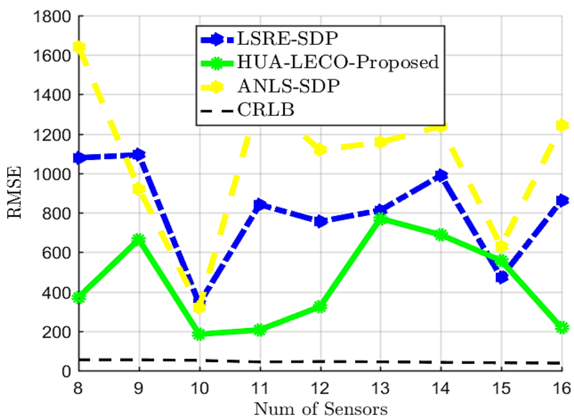

Figure 5. Comparison of RMSE versus the number of sensor nodes for different methods considering noise level of 3dB

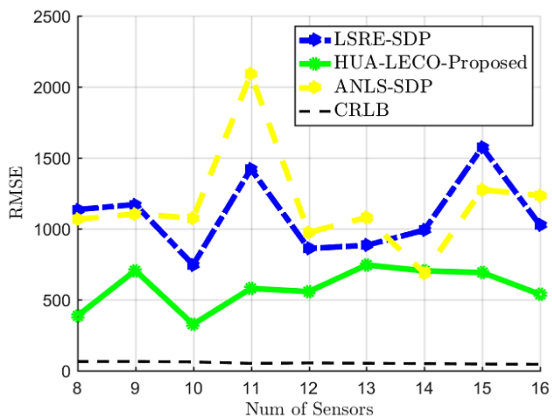

Figure 6. Comparison of RMSE versus the number of sensor nodes for different methods considering noise level of 5dB

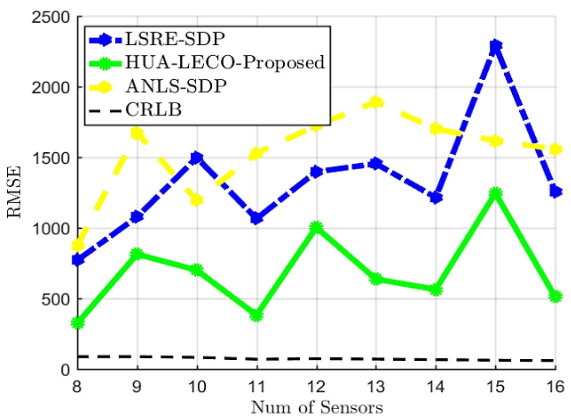

Figure 7. Comparison of RMSE versus the number of sensor nodes for different methods considering noise level of 7dB

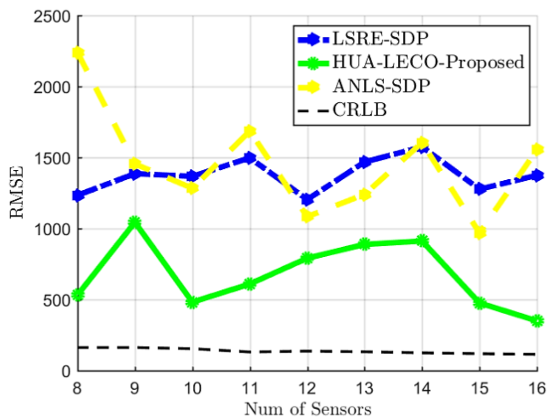

Figure 8. Comparison of RMSE versus the number of sensor nodes for different methods considering noise level of 9dB

5. CONCLUSION

The significance of mobile sensor node localization is extremely high in WSN. The continuous change in mobile sensor node position can vary strength of radio signals based on an unknown decay factor under high uncertainties regarding position of mobile sensor node. Moreover, few works are presented related to localization of sensor nodes in terms of error minimization. However, localization of mobile sensor nodes under high uncertainties using these models is not that efficient due to complexity of continuous varying RSS. Therefore, a detailed study is conducted in this work to determine location of unknown mobile sensor node using the proposed HUA-LECO model. Moreover, varied works are presented related to error minimization to determine sensor node location such as LSRE through SDP optimization and ANLS-SDP model. However, in this work, a study to determine the localization of mobile sensor nodes and the impact of noise factor and Monte Carlo iterations on localization error is observed against the varied number of sensors from the obtained multi-measurements using the proposed HUA-LECO model. An iterative weight updation approach is used based on the Monte Carlo Simulations to minimize the root mean square error and achieve fast convergence. Simulation performance results demonstrate a significant improvement in terms of mobile sensor node localization with minimum localization error in comparison with ANLS-SDP and LSRE-SDP models. The major contribution of this study is the estimation of mobile sensor node location when RSS is continuously varying under high uncertainties and minimization of localization error in comparison with ANLS-SDP and LSRE-SDP models. Another contribution is the observation of impact of varying noise levels and Monte Carlo iterations on localization error. In future work, impact of several environmental conditions like multi-path loss and fading can be considered.

REFERENCES

[1] R. Rathna, "Simple clustering for wireless sensor networks," *Cybernetics and Information Technologies*, vol. 16, no. 1, pp. 57–72, Mar. 2016, doi: 10.1515/cait-2016-0004.

[2] A. Tripathi, H. P. Gupta, T. Dutta, R. Mishra, K. K. Shukla, and S. Jit, "Coverage and connectivity in WSNs: a survey, research issues and challenges," *IEEE Access*, vol. 6, pp. 26971–26992, 2018, doi: 10.1109/access.2018.2833632.

[3] Z. Sun, Y. Liu, and L. Tao, "Attack localization task allocation in wireless sensor networks based on multi-objective binary particle swarm optimization," *Journal of Network and Computer Applications*, vol. 112, pp. 29–40, Jun. 2018, doi: 10.1016/j.jnca.2018.03.023.

[4] J. Won and E. Bertino, "Robust sensor localization against known sensor position attacks," *IEEE Transactions on Mobile Computing*, vol. 18, no. 12, pp. 2954–2967, Dec. 2019, doi: 10.1109/tmc.2018.2883578.

[5] S. Savazzi, U. Spagnolini, L. Goratti, D. Molteni, M. Latva-aho, and M. Nicoli, "Ultra-wide band sensor networks in oil and gas explorations," *IEEE Communications Magazine*, vol. 51, no. 4, pp. 150–160, Apr. 2013, doi: 10.1109/mcom.2013.6495774.

[6] G. Werner-Allen *et al.*, "Deploying a wireless sensor network on an active volcano," *IEEE Internet Computing*, vol. 10, no. 2, pp. 18–25, Mar. 2006, doi: 10.1109/mic.2006.26.

[7] R. Bhatt, P. Maheshwary, P. Shukla, P. Shukla, M. Shrivastava, and S. Changlani, "Implementation of fruit y optimization algorithm (FFOA) to escalate the attacking efciency of node capture attack in wireless sensor networks (WSN)," *Computer Communications*, vol. 149, pp. 134–145, Jan. 2020, doi: 10.1016/j.comcom.2019.09.007.

[8] X. Liu, S. Su, F. Han, Y. Liu, and Z. Pan, "A range-based secure localization algorithm for wireless sensor networks," *IEEE Sensors Journal*, vol. 19, no. 2, pp. 785–796, Jan. 2019, doi: 10.1109/jsen.2018.2877306.

[9] S. A. AlRoomi, I. Ahmad, and T. Dimitriou, "Secure localization using hypothesis testing in wireless networks," *Ad Hoc Networks*, vol. 74, pp. 47–56, May 2018, doi: 10.1016/j.adhoc.2018.03.008.

[10] A. Allouch, O. Cheikhrouhou, A. Koubaa, M. Khalgui, and T. Abbes, "MAVSec: securing the MAVLink protocol for ardupilot/PX4 unmanned aerial systems," in *2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC)*, Jun. 2019, pp. 621–628, doi: 10.1109/iwcmc.2019.8766667.

[11] O. Cheikhrouhou, G. M. Bhatti, and R. Alroobaea, "A hybrid DV-hop algorithm using RSSI for localization in large-scale wireless sensor networks," *Sensors*, vol. 18, no. 5, p. 1469, May 2018, doi: 10.3390/s18051469.

[12] S. Messous, H. Liouane, and N. Liouane, "Improvement of DV-Hop localization algorithm for randomly deployed wireless sensor networks," *Telecommunication Systems*, vol. 73, no. 1, pp. 75–86, Jul. 2019, doi: 10.1007/s11235-019-00592-6.

[13] D. Han, Y. Yu, K.-C. Li, and R. F. de Mello, "Enhancing the sensor node localization algorithm based on improved DV-hop and DE algorithms in wireless sensor networks," *Sensors*, vol. 20, no. 2, p. 343, Jan. 2020, doi: 10.3390/s20020343.

[14] A. P. Das and S. M. Thampi, "Fault-resilient localization for underwater sensor networks," *Ad Hoc Networks*, vol. 55, pp. 132–142, Feb. 2017, doi: 10.1016/j.adhoc.2016.09.003.

[15] S. J. Bhat and K. V Santhosh, "Is localization of wireless sensor networks in irregular elds a challenge?," *Wireless Personal Communications*, vol. 114, no. 3, pp. 2017–2042, May 2020, doi: 10.1007/s11277-020-07460-6.

[16] J. Kumari, P. Kumar, and S. K. Singh, "Localization in three-dimensional wireless sensor networks: a survey," *The Journal of Supercomputing*, vol. 75, no. 8, pp. 5040–5083, Feb. 2019, doi: 10.1007/s11227-019-02781-1.

[17] K. Gao, J. Zhu, and Z. Xu, "Majorization-minimization-based target localization problem from range measurements," *IEEE Communications Letters*, vol. 24, no. 3, pp. 558–562, Mar. 2020, doi: 10.1109/lcomm.2019.2963834.

[18] A. P. Behera, A. Singh, S. Verma, and M. Kumar, "Manifold learning with localized procrustes analysis based WSN localization," *IEEE Sensors Letters*, vol. 4, no. 10, pp. 1–4, Oct. 2020, doi: 10.1109/lsens.2020.3025360.

[19] S. J. Bhat and K. V Santhosh, "A method for fault tolerant localization of heterogeneous wireless sensor networks," *IEEE Access*, vol. 9, pp. 37054–37063, 2021, doi: 10.1109/access.2021.3063160.

[20] A. Bochem and H. Zhang, "Robustnessenhanced sensor assisted Monte Carlo localization for wireless sensor networks and the internet of things," *IEEE Access*, vol. 10, pp. 33408–33420, 2022, doi: 10.1109/access.2022.3162288.

[21] H. Liouane, S. Messous, O. Cheikhrouhou, M. Baz, and H. Hamam, "Regularized least square multi-hops localization algorithm for wireless sensor networks," *IEEE Access*, vol. 9, pp. 136406–136418, 2021, doi: 10.1109/access.2021.3116767.

[22] K. Sabale and S. Mini, "Transmission power control for anchor-assisted localization in wireless sensor networks," *IEEE Sensors*

Journal, vol. 21, no. 8, pp. 10102–10111, Apr. 2021, doi: 10.1109/jsen.2021.3054372.
[23] N. R. Thejaswini and G. Muthupandi, "Dynamic noisy measurement aware localization model for wireless sensor networks," *Journal of Interconnection Networks*, vol. 22, no. 04, May 2022, doi: 10.1142/s0219265921500328.
[24] Q. Luo, Y. Peng, J. Li, and X. Peng, "RSSI-based localization through uncertain data mapping for wireless sensor networks," *IEEE Sensors Journal*, vol. 16, no. 9, pp. 3155–3162, May 2016, doi: 10.1109/jsen.2016.2524532.
[25] T. Wang, H. Ding, H. Xiong, and L. Zheng, "A compensated multi-anchors TOF-based localization algorithm for asynchronous wireless sensor networks," *IEEE Access*, vol. 7, pp. 64162–64176, 2019, doi: 10.1109/access.2019.2917505.
[26] T. Wang, H. Xiong, H. Ding, and L. Zheng, "TDOA-based joint synchronization and localization algorithm for asynchronous wireless sensor networks," *IEEE Transactions on Communications*, vol. 68, no. 5, pp. 3107–3124, May 2020, doi: 10.1109/tcomm.2020.2973961.
[27] W. Ding, S. Chang, and J. Li, "A novel weighted localization method in wireless sensor networks based on hybrid RSS/AoA measurements," *IEEE Access*, vol. 9, pp. 150677–150685, 2021, doi: 10.1109/access.2021.3126148.
[28] L. Hu and D. Evans, "Localization for mobile sensor networks," in *Proceedings of the 10th annual international conference on Mobile computing and networking*, Sep. 2004, pp. 45–57, doi: 10.1145/1023720.1023726.
[29] M. Qin and R. Zhu, "A Monte Carlo localization method based on differential evolution optimization applied into economic forecasting in mobile wireless sensor networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2018, no. 1, pp. 1–9, Feb. 2018, doi: 10.1186/s13638-018-1037-1.
[30] Y. Zhang, L. Cui, and S. Chai, "Energy-ef cient localization for mobile sensor networks based on RSS and historical information," in *The 27th Chinese Control and Decision Conference (CCDC)*, May 2015, pp. 5246–251, doi: 10.1109/ccdc.2015.7162860.
[31] S. Hartung, A. Kellner, K. Rieck, and D. Hogrefe, "Applied sensorassisted Monte Carlo localization for mobile wireless sensor networks," in *2016 IEEE Wireless Communications and Networking Conference*, Apr. 2016, pp. 181–192, doi: 10.1109/wcnc.2016.7564906.
[32] Z. Munadhil, S. K. Gharghan, A. H. Mutlag, A. Al-Naji, and J. Chahl, "Neural network-based Alzheimer's patient localization for wireless sensor network in an indoor environment," *IEEE Access*, vol. 8, pp. 150527–150538, 2020, doi: 10.1109/access.2020.3016832.
[33] P. Rajanikanth and K. S. Reddy, "An efficient routing mechanism for node localization, cluster based approach and data aggregation to extend WSN lifetime," *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 1, Feb. 2022, doi: 10.22266/ijies2022.0228.28.
[34] J. Chen, S. H. Sackey, J. A. Ansere, X. Zhang, and A. Ayush, "A neighborhood grid clustering algorithm for solving localization problem in WSN using genetic algorithm," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–13, Jun. 2022, doi: 10.1155/2022/8552142.
[35] S. P. Racharla and J. Kalaivani, "A review on localization problems in wireless sensor network: algorithmic and performance analysis," in *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, May 2021, pp. 31–35, doi: 10.1109/icspc51351.2021.9451770.
[36] J. Shi, G. Wang, and L. Jin, "Least squared relative error estimator for RSS based localization with unknown transmit power," *IEEE Signal Processing Letters*, vol. 27, pp. 1165–1169, 2020, doi: 10.1109/lsp.2020.3005298.
[37] J. Shi, G. Wang, and L. Jin, "Robust semidefinite relaxation method for energy-based source localization: known and unknown decay factor cases," *IEEE Access*, vol. 7, pp. 163740–163748, 2019, doi: 10.1109/access.2019.2952641.
[38] Y. Xu and W. Yin, "A globally convergent algorithm for nonconvex optimization based on block coordinate update," *Journal of Scientific Computing*, vol. 72, no. 2, pp. 700–734, Feb. 2017, doi: 10.1007/s10915-017-0376-0.
[39] S. Tomic, M. Beko, and R. Dinis, "RSS-based localization in wireless sensor networks using convex relaxation: noncooperative and cooperative schemes," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 5, pp. 2037–2050, May 2015, doi: 10.1109/tvt.2014.2334397.

BIOGRAPHIES OF AUTHOR

Raja Thejaswini Nandyala currently working as assistant professor at Gopalan college of engineering & management, Bangalore. Overall, 15 years of teaching experience. Areas of interest are wireless sensor network, VLSI design. Received B. E. and M. Tech degree form JNTU, Hyderabad. Published journal "Dynamic Noisy Measurement Aware Localization Model" in Journal of Interconnection Networks. She can be contacted at this email: thejas.nannyal@gmail.com.

Dr. G. Muthupandi received a B.E. degree in Electronics and Communication Engineering from MK University, TN (2001). and M.E. degree in Computer and Communication Engineering from PSNACET-Anna University, TN (2007). Completed his Ph.D. degree in 2018 in Information and Communication Engineering from Anna University, He is currently working as an Associate Professor in the Department of Electronics and Communication Engineering at Presidency University, Bangalore. His area of research includes Digital Image Signal Processing and VLSI signal Processing, wireless sensor networks. He can be contacted at this email: muthupandi@presidencyuniversity.in.